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Health assessment of transformers using online and offline parameters

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Abstract

Distribution transformers at substations are crucial assets in power system, whose failure can cause major operational disruptions, safety risks, and economic losses, thus making effective condition assessment essential for ensuring reliability and minimizing outages. This paper presents Supervisory Control and Data Acquisition (SCADA)-based transformer Health Index (HI) method that combines both Offline Parameters (OFPs) which include transformer age, historical loading, maintenance history, and environmental conditions and Online Parameters (ONPs) which incorporate real-time operational stresses like voltage, current, active power, oil temperature, and winding temperature. The proposed HI formulation applies a rule-based, explainable scoring and weighting scheme to combine OFPs and ONPs into a single normalized metric where based on published failure statistics and utility-specific evidence, a weightage of 30% for OFPs and 70% for ONPs is adopted, emphasizing operational stress while accounting for long-term degradation. The computed HI is categorized as Good (85–100%), Fair (65–85%), Poor (50–65%), or Very Poor (0–50%). The method is tested using one year of data from two parallel 66/11 kV, 30 MVA power transformers and overall HI values of 0.598 and 0.567 for Transformer-1 and Transformer-2 respectively classify that both are in the fair condition category, suggesting the need for enhanced inspection rather than immediate replacement, while degradation-rate analysis confirms stable long-term operation.

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1. Introduction

Distribution transformers are among the most critical and capital-intensive components of electrical power systems, and their unexpected failure can lead to prolonged outages, substantial economic losses, and cascading system instability. The paper [1] discusses how transformers are crucial to power system reliability, represent significant investments for utilities, and how their failure can cause financial, service, and operational impacts on the grid. To mitigate these risks, transformer Health Index (HI) methodologies have been widely adopted to aggregate multiple condition indicators into a single quantitative metric that supports asset ranking, maintenance prioritization, and lifecycle management decisions [2]. HI-based approaches are particularly effective because transformer degradation results from complex interactions among thermal, electrical, mechanical, and chemical stress mechanisms, which cannot be adequately captured by any single diagnostic technique [2], [3]. Conventional transformer condition assessment frameworks rely predominantly on offline diagnostic measurements such as dissolved gas analysis (DGA), frequency response analysis (FRA), partial discharge (PD) measurements, and oil quality testing [2][3]. These techniques offer high diagnostic accuracy and fault specificity by directly revealing internal electrical, thermal, and mechanical abnormalities. However, they require specialized equipment, scheduled testing, and expert interpretation, which often limits their inspection frequency, particularly in utilities with constrained financial and technical resources [3]. These limitations have motivated increasing interest in complementary monitoring approaches based on continuously available operational data. Recent studies demonstrate that transformer insulation aging and loss of life are fun-

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damentally governed by thermal stress, which is directly influenced by electrical loading, ambient temperature, and cooling conditions [4]. The degradation of cellulose insulation accelerates exponentially with increasing hot-spot temperature, making load history a critical determinant of transformer aging. Consequently, incorporating operational history and loading profiles into HI formulations has been shown to improve the representation of long-term degradation trends and residual life estimation [4]. This provides a strong theoretical basis for leveraging SCADA-recorded parameters such as current, voltage, power, and temperature as indirect yet informative indicators of transformer health. SCADA systems continuously record operational measurements at high temporal resolution, making them attractive for online transformer health assessment. Although SCADA data were not originally intended for asset diagnostics, prior research indicates that statistical features extracted from load profiles, voltage deviations, and thermal measurements can effectively reflect abnormal operating conditions and cumulative stress exposure [5]. This capability is particularly relevant for developing power systems, where advanced condition monitoring infrastructure may be limited but SCADA deployment is increasingly widespread across transmission and distribution networks [5]. Despite the growing importance of operational data, dissolved gas analysis remains a cornerstone of transformer condition monitoring due to its ability to detect incipient thermal and electrical faults through characteristic gas patterns dissolved in transformer oil [6]. Accordingly, modern HI frameworks increasingly adopt an explicit separation between online operational health components derived from SCADA data and offline diagnostic health components derived from periodic testing [2][3]. This separation enhances interpretability, improves diagnostic confidence, and enables flexible implementation depending on data availability and utility practices. For practical utility deployment, recent literature emphasizes the importance of rule-based and explainable HI formulations rather than purely black-box machine learning approaches [3][7]. Rule-based scoring systems grounded in transformer aging physics, such as overload duration penalties, thermal threshold violations, and voltage deviation limits, offer transparency, reproducibility, and regulatory acceptability [8]. These characteristics are essential for integrating HI tools into existing utility asset management systems and for fostering operator confidence in decision-support applications [7]. Furthermore, transformer health indices are increasingly incorporated into risk-based maintenance and replacement optimization frameworks, where HI values are used to estimate failure probability and associated economic risk [9]. By linking condition assessment with probabilistic risk analysis, utilities can prioritize maintenance actions, defer unnecessary asset replacement, and improve long-term investment planning [10][11][12]. The findings of this study are corroborated by recent transformer health index literature as in the Table 1.

2. Research methodology

2.1. SCADA data characteristics

The dataset used in this study consists of time-stamped Supervisory Control and Data Acquisition (SCADA) measurements obtained from an operational utility substation comprising two parallel-connected power transformers operating under similar grid conditions. The SCADA records span a continuous period from Poush 2081 to Poush 2082 (B.S.), providing multiple years of real-world operational data across varying seasonal and loading conditions. SCADA systems continuously monitor key electrical and thermal parameters required for operational supervision and control. The recorded variables include line voltage, line current, active power, top oil temperature, and winding temperature. These parameters directly reflect transformer loading conditions, electrical stress, and thermal behavior, which are the dominant factors influencing transformer aging and degradation. Measurements were recorded at high temporal resolution, typically ranging from several seconds to a few minutes, and were stored in comma-separated values (CSV) format. High-resolution SCADA data capture both steady-state operating trends and short-duration variations caused by load fluctuations, network disturbances, and ambient conditions. While such granularity is valuable for operational monitoring, systematic preprocessing is necessary to extract meaningful health-related indicators suitable for long-term asset assessment and condition monitoring.

2.2. Data cleaning and quality assurance

Raw SCADA datasets often contain imperfections arising from communication failures, sensor malfunctions, synchronization errors, and logging inconsistencies. If left unaddressed, these issues can propagate into derived indicators and compromise the reliability of the Health Index computation. Therefore, a structured data cleaning and quality assurance procedure was implemented prior to analysis. Redundant, unnamed, or non-informative columns introduced during data acquisition or export were first removed to ensure a consistent dataset structure. All operational parameters were explicitly converted to numeric format to prevent errors caused by mixed data types or string-encoded numerical values. Rows containing missing values, non-physical readings, or invalid entries were eliminated to maintain data integrity. A complete-case analysis strategy was adopted, whereby only records with valid measure-

Table 1: State of the art with gap and contribution of this study

Ref.	Focus	Gap	Contribution
[11]	Review of AI & conventional HI methods	No SCADA-based practical implementation	SCADA-based, rule-driven HI for real grids
[13]	Real-time HI prediction using ML	Requires advanced infrastructure	Physics-aligned HI using existing SCADA data
[14]	ML prediction with class balancing	Limited interpretability & physical insight	Hybrid weighted HI with clear operational vs offline contribution
[5]	IoT monitoring for predictive maintenance	Focus on sensors, not HI weighting	Defines HI linking operational parameters to degradation
[15]	Overview of weighted-score HI methods	No separation of stress vs aging	Explicit Online/Offline HI separation

ments across all required variables were retained. This approach avoids the introduction of artificial trends or statistical bias that may arise from interpolation or imputation, which is particularly important for transformer health assessment, where extreme values often carry diagnostic significance.

2.3. Time synchronization and daily aggregation

SCADA datasets frequently store date and time information in separate fields, which can complicate temporal alignment and analysis. In this study, the date and time fields were merged into a unified timestamp to create a continuous time-series representation of transformer operation. This unified timeline enabled consistent resampling and aggregation of measurements. To align the data with the thermal aging characteristics of power transformers, high-resolution SCADA measurements were resampled on a daily basis. For each operational parameter, the daily mean value was computed as:

$$\bar{x}_d = \frac{1}{N_d} \sum_{i=1}^{N_d} x_i \tag{1}$$

where represents individual SCADA samples within day d, and N_d denotes the total number of samples recorded during that day. Daily aggregation serves two key purposes. First, it suppresses short-term transient fluctuations that do not significantly contribute to long-term insulation aging. Second, it aligns the data with the thermal time constants of transformer oil and winding insulation, which respond to sustained loading rather than instantaneous disturbances. This makes daily statistics particularly suitable for Health Index formulation and loss-of-life estimation.

2.4. Derived operational indicators

2.4.1. Temperature normalization

Transformer insulation degradation is strongly dependent on operating temperature, particularly winding hotspot temperature and top oil temperature. To allow consistent comparison across operating conditions and transformer ratings, measured temperatures were normalized relative to their rated limits using:

$$T_{\text{norm}} = \frac{T_{\text{measured}}}{T_{\text{rated}}} \tag{2}$$

This normalization converts absolute temperature values into dimensionless indicators that directly represent proximity to thermal design limits. Normalized temperature values exceeding unity indicate operation beyond rated conditions, corresponding to accelerated insulation aging and reduced transformer lifetime. Values approaching unity indicate elevated thermal stress when sustained over extended periods.

2.4.2. Power factor estimation

Power factor is an important operational indicator reflecting the efficiency of power transfer and the reactive loading imposed on the transformer. Using SCADA measurements, the power factor was estimated as:

$$\cos\phi = \frac{MW \times 10^6}{\sqrt{3} \times KV \times 10^3 \times A} \tag{3}$$

where MW is the active power, KV is the line voltage, and A is the line current. A low power factor implies higher current for the same active power delivery, resulting in increased copper losses, elevated winding temperature, and additional thermal stress. Persistent low power factor operation can therefore accelerate transformer aging even when active power loading appears moderate.

2.4.3. *Efficiency and deviation analysis*

Transformer efficiency provides an indirect measure of internal losses and overall operational health. Efficiency was calculated as:

$$\eta = \frac{P_{\text{out}}}{P_{\text{in}}} \times 100 \tag{4}$$

where P_{out} and P_{in} denote output and input power, respectively. To isolate degradation-related changes from inherent design characteristics, the deviation from rated efficiency was defined as:

$$\Delta\eta = \left| \frac{\eta_{\text{rated}} - \eta}{\eta_{\text{rated}}} \right| \tag{5}$$

This relative deviation metric captures incremental deterioration caused by increased losses, insulation aging, or abnormal operating conditions, independent of the transformer's nominal efficiency rating. Larger deviations indicate potential degradation or unfavorable operating regimes.

2.4.4. *Average loading index*

Electrical loading is a primary driver of both thermal and mechanical stress in transformers. The average loading index was computed relative to the rated capacity as:

$$L_{\text{avg}} = \frac{P_{\text{out}}}{P_{\text{rated}}} \times 100 \tag{6}$$

This index provides a normalized measure of transformer utilization and facilitates comparison across units with different ratings. Sustained high loading increases winding temperature, accelerates insulation aging, and exacerbates mechanical forces during transient events. When evaluated on a daily basis, the average loading index offers a clear representation of long-term operational stress and its contribution to transformer health degradation.

3. Health index formulation and scoring methodology

Transformer failure statistics reported in recent literature consistently emphasize the dominant role of aging and loading related stresses in transformer degradation. According to [9], transformer age and overload jointly contribute to approximately 35% of total transformer failures, a combined effect commonly categorized as aging-related degradation. These factors are typically classified as Offline Parameters (OFPs), as they vary slowly over time and represent inherent asset characteristics rather than instantaneous operating conditions. Similar observations are reported in [16], where nearly 25% of transformer failures are attributed to aging and loading stress. Furthermore, [17] indicates that age and other non-operational factors account for less than 28% of failures, while [18] highlights that improper or inadequate maintenance alone contributes nearly 29% of transformer outages. Field failure statistics obtained from the Nepal Electricity Authority (NEA) further confirms these findings, showing that OFPs contribute approximately 29.45% of recorded transformer failures. These statistics emphasizes the importance of incorporating asset-related offline data in transformer condition assessment. However, failure mechanisms are not governed solely by long-term degradation; real-time operational stress, particularly thermal stress arising from electrical loading, plays a decisive role in accelerating insulation aging and failure probability. Consequently, a combined evaluation of Offline Parameters (OFPs) and Online Parameters (ONPs) is essential for computing a reliable and practically meaningful transformer Health Index. It is noted that the relative influence of OFPs and ONPs may vary across utilities depending on operating practices, environmental conditions, and historical maintenance strategies. Therefore, the weighting scheme adopted in this study reflects both published failure statistics and utility - specific operational evidence.

3.1. Overall health index formulation

Based on the aforementioned failure statistics and engineering judgment, a weight of 30% is assigned to Offline Parameters, while 70% is allocated to Online Parameters. This allocation ensures that real time operational stress dominates the health assessment, while long-term degradation mechanisms are still adequately represented.

The overall transformer Health Index is defined as:

$$HI = 0.3\, HI_{\text{OFP}} + 0.7\, HI_{\text{ONP}} \tag{7}$$

This formulation reflects the fact that transformer deterioration is strongly driven by thermal stress induced by present operating conditions, superimposed on the cumulative effects of aging and maintenance history.

3.2. Offline parameters (OFPs)

Offline Parameters represent slowly varying asset characteristics that significantly influence transformer reliability and service life. Transformer condition is influenced by multiple factors. Age affects insulation integrity and failure likelihood, while historical loading, especially repeated overloads, adds cumulative thermal and mechanical stress. Maintenance practices play a critical role, as poor or infrequent servicing accelerates insulation aging and defect development. Transformer type, such as oil-immersed or dry-type, impacts cooling efficiency and thermal endurance, and site-specific environmental conditions including temperature, humidity, pollution, and altitude further affect thermal stress and insulation deterioration.

A weighted method that gives each parameter importance according to its effect on transformer health can be used to calculate the HI by considering all of the OFPs. The Offline Health Index (HI_{OFP}) can be calculated using the following generalized formula:

$$HI_{\text{OFP}} = \frac{1}{S_{\max}} \left(\frac{\sum_{i=1}^{5} S_{pi} \cdot W_{pi}}{\sum_{i=1}^{5} W_{pi}} \right) \tag{8}$$

S_{pi} is the score of each parameter based on the maximum permissible limit and $S_{\max}$ the maximum score for OFP as introduced in Table 2. P_i denotes the ith parameter considered in the Health Index (HI) formulation. Each P_i represents an individual Offline Parameter (OFP) or Online Parameter (ONP) included in the scoring methodology in Table 2 and 3.

3.3. Online parameters (ONPs)

Online Parameters represent real-time operational conditions that directly affects transformer thermal behavior and instantaneous degradation process. In practical utility environments, transformer deterioration is predominantly governed by electro-thermal stress, which is driven by electrical loading and cooling effectiveness. In this study, the online parameters (ONPs) are derived from SCADA measurements to ensure consistency and practical relevance. The main parameters include line voltage, which affects core losses and dielectric stress; line current, indicating transformer loading and copper losses; active power, reflecting overall load severity; oil temperature, showing the bulk thermal state and cooling performance; and winding temperature, the critical factor driving insulation aging. Together, these parameters capture the main electro-thermal stresses experienced by the transformer in real operating conditions. By considering all the online parameters, the health index can be computed by using Equation 9 as,

$$HI_{\text{ONP}} = \frac{1}{S_{\max}} \left(\frac{\sum_{i=6}^{9} S_{pi} \cdot W_{pi}}{\sum_{i=6}^{9} W_{pi}} \right) \tag{9}$$

Where, S_{pi} is the score of each parameter based on the maximum permissible limit and S_{max} the maximum score for the online parameter as introduced in Table 3.

3.4. Transformer health state classification

The computed Health Index is normalized and expressed in percentage form to facilitate intuitive interpretation and maintenance decision-making. Transformer health is classified into five categories based on the Health Index (HI). A Very Good condition (85–100%) indicates that the transformer is operating satisfactorily and requires only normal maintenance. A Good condition (65–85%) suggests the need for increased periodic maintenance to ensure continued reliable operation. A Fair condition (55–65%) reflects noticeable degradation and requires enhanced inspection and diagnostic testing. A Poor condition (40–55%) indicates significant deterioration, and the replacement process should be initiated. A Very Poor condition (0–40%) represents a critical state where immediate risk assessment and corrective action are necessary to prevent potential failure. This classification guideline enables utilities to prioritize maintenance activities, optimize asset replacement planning, and improve overall system reliability using readily available SCADA data.

3.5. Degradation rate calculation

Transformer health is monitored not only through absolute Health Index values but also by analyzing temporal changes, known as the degradation rate. The degradation rate quantifies the daily change in transformer health, providing insights into both gradual deterioration and sudden declines.

3.5.1. Daily degradation rate

The daily degradation rate for each transformer is defined as,

$$\Delta HI_t = HI_t - HI_{t-1} \tag{10}$$

where HI_t and HI_{t-1} denote the Health Index on day t and day $t-1$, respectively.

A positive or zero value of HI_t indicates stable or improving health, whereas a negative value reflects deterioration, with larger negative values corresponding to faster degradation. The daily degradation rate is categorized into four discrete states to provide actionable insights:

Table 2: Weightage for OFP

Pi	P	S				
		4	3	2	1	W
1	Age, years	0–5	6–10	11–15	16–20	4
2	Average loading, %	< 60	61–75	76–85	> 85	2
3	Mpa	1	2	3	> 3	3
4	Type of transformer	0	1	2	> 2	4
5	Location	*A*	*I*	*R*	*B*	1

Table 3: Weightage for ONP

Pi	ONP,Pu	S				
		4	3	2	1	W
6	$\cos\phi$	> 0.95	0.8–0.95	0.6–0.8	< 0.6	1
7	Dev. in η	< 0.005	0.005–0.0075	0.0075–0.01	> 0.01	4
8	Wdg. temp.	< 0.6	0.6–0.8	0.8–1.0	> 1.0	1
9	Oil temp.	< 0.6	0.6–0.8	0.8–1.0	> 1.0	4

This classification enables early detection of both gradual and severe health deterioration, facilitating timely maintenance interventions.

3.5.2. Monthly degradation rate

The monthly degradation rate quantifies long-term trends in transformer health by comparing the average HI between consecutive months as in Equation 11.

$$\Delta HI_{\text{monthly},m} = HI_{\text{monthly},m} - HI_{\text{monthly},m-1} \quad (11)$$

where $HI_{\text{monthly},m}$ is the mean Health Index of month m.

Similar to the daily classification, the monthly degradation rate is divided into four states:

Monthly aggregation smooths short-term fluctuations and highlights persistent trends, enabling strategic maintenance planning and informed operational decisions.

3.6. Overall workflow of the study

The flowchart illustrates a structured computational framework for transformer Health Index (HI) evaluation that integrates real-time SCADA-based online parameters (voltage, current, active power, oil temperature, and winding temperature) with offline asset parameters (age, loading history, maximum permissible amperage, transformer type, and location) to produce a comprehensive condition assessment and maintenance decision output. The process begins with data acquisition, followed by rigorous data cleaning and quality assurance including removal of missing and invalid entries, numeric conversion, time synchronization, and daily aggregation to ensure statistical reliability and noise reduction. Online parameters are then mathematically derived into stress indicators such as loading percentage and thermal severity indices, while offline parameters are mapped to predefined condition scores using standardized scoring tables. Each parameter is assigned a weighting factor reflecting its relative influence on insulation aging and failure probability, and weighted summation is performed separately to compute the Online Health Index (HI_{ONP}) and Offline Health Index (HI_{OFP}). These two components are subsequently integrated through a weighted combination model to obtain the overall HI, which captures both short-term operational stress and long-term degradation characteristics. Finally, the overall HI is classified into health state categories to support maintenance prioritization, degradation trend monitoring, and asset management decision-making, thereby transforming heterogeneous operational and asset data into a quantitative, risk-informed reliability indicator suitable for condition-based maintenance implementation.

4. Results and discussions

The study considers Two three-phase 66/11 kV transformer rated at 24 MVA under ONAN cooling and 30 MVA under ONAF cooling, operating at a frequency of 50 Hz. The rated currents are 209.95 A and 1259.67 A on the high-voltage (HV) and low-voltage (LV) sides,

Table 4: State of health of transformer

% HI	State of Health	Requirement
85–100	Very Good	Normal Maintenance
65–85	Good	Increase Periodic Maintenance
55–65	Fair	Increase Inspection and Diagnostic Testing
40–55	Poor	Start Process to Replace
0–40	Very Poor	Immediately Assess Risk

Table 5: State of health of transformer based on ΔHI_t

ΔHI_t	Degradation State	Interpretation
≥ 0	Stable / Improving	Transformer health is stable or improving.
$-0.2 \leq \Delta HI_t < 0$	Slow Degradation	Minor deterioration; routine monitoring recommended.
$-0.5 \leq \Delta HI_t < -0.2$	Moderate Degradation	Noticeable deterioration; preventive maintenance suggested.
< -0.5	Severe Degradation	Rapid deterioration; immediate assessment and corrective action required.

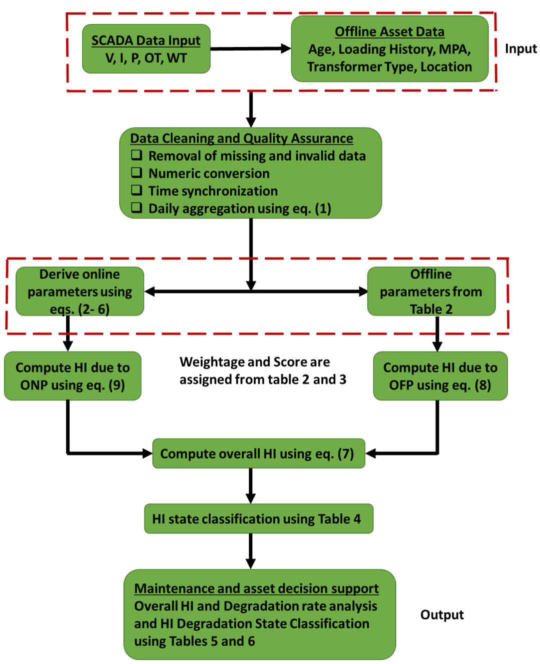

Figure 1: Flowchart of the study

respectively. The transformer has a vector group of YNyn0 and a percentage impedance of 10.72% on a 30 MVA base. It is designed for a maximum ambient temperature of 45 °C, with allowable top-oil and average winding temperature rises of 50 °C and 55 °C, respectively. The no-load and load losses at full load (30 MVA) are 12.445 kW and 93.793 kW, respectively. Insulation levels comply with IEC 60076, being 325 kVp/140 kV (LI/AC) for the 66 kV side and 95 kVp/28 kV for the 11 kV side. The transformer was manufactured in 2019. Two identical units are considered for the health index evaluation.

4.1. Data trending

The oil and winding temperature variations with different time instants cumulative sum (daily) shown in Figures 2 and 3 are used to check transformer thermal performance. Transformers 1 (T1) and Transformer 2 (T2) both indicate similar temperature trends and typically function within a proper thermal temperature range of 35 °C to 50 °C while operating under the normal conditions. T1, on the other hand, continuously operates slightly higher oil temperatures than the T2, suggesting slightly large thermal stress. Jestha 2082 (Figure 2) shows an unusual reduction in the temperature for Transformer 1 to about 20 °C, which is probably caused by a outage or sensor abnormalities. Additionally, during Chaitra 2081 and Ashadh 2082, there are temperature variations that reaches to 60 °C abruptly, which correlate to times of increased loading. As shown in Figures 4, 6, 8, 9, and 10, electrical loading characteristics can be analyzed using output current, output power, input current, input power, and average loading. Stable operational behavior seen in these performance matrices has great mutual uniformity. After remaining unchanged for a long time until Shrawan 2082, loading levels gradually increases until reaching their highest peak point during Ashwin 2082 and Mangsir 2082. There is a noticeable abnormal conditions in Mangsir 2082, as in Figures 6 and 10, show that T2 has an excessive output power

Table 6: State of health of transformer based on $\Delta HI_{\text{monthly},m}$

$\Delta HI_{\text{monthly},m}$	**Degradation State**	**Interpretation**
≥ 0	Stable / Improving	Transformer is maintaining or improving its health over the month.
$-0.2 \leq \Delta HI_{\text{monthly},m} < 0$	Slow Degradation	Minor monthly deterioration; monitoring recommended.
$-0.5 \leq \Delta HI_{\text{monthly},m} < -0.2$	Moderate Degradation	Noticeable deterioration; preventive maintenance suggested.
< -0.5	Severe Degradation	Rapid deterioration; immediate assessment and corrective action required.

Table 7: Transformer's nameplate data

Parameter	**Value**
Transformer Rating (ONAN)	24 MVA
Transformer Rating (ONAF)	30 MVA
Voltage Ratio	66 / 11 kV
Rated Current – HV Side	209.95 A
Rated Current – LV Side	1259.67 A
Number of Phases	3
Frequency	50 Hz
Cooling Method	ONAN / ONAF
Vector Group	YNyn0
Percentage Impedance (at 30 MVA)	10.72 %
Reference Ambient Temperature	45 °C
Top Oil Temperature Rise	50 °C
Average Winding Temperature Rise	55 °C
No-Load Loss	12.445 kW
Load Loss at 30 MVA	93.793 kW
Insulation Level – HV (66 kV)	LI 325 kVp / AC 140 kV
Insulation Level – LV (11 kV)	LI 95 kVp / AC 28 kV
Year of Manufacture	2019
Manufacturer	Schneider Electric

spike and average loading of more than 300%. Under normal operating conditions, output power ranges from 10 MW to 20 MW, while average loading stays between 50% and 80%. Figure 11 and 12 show the behavior of system efficiency. Transformer's efficiency is physically limited to less than 100%, yet Figure 11 indicates the unreasonably high efficiency values due to sensor faults and abnormal conditions, especially for T2 in Mangsir 2082, ranging from 200% to 500%. Figure 12 provides additional evidence of notable variations in efficiency during this time frame. Measurement mistakes, sensor desynchronization, or data discrepancies during sudden power swings for the load are probably the causes of these anomalies. A severe overvoltage event in Falgun 2081, an unusual temperature reduction in T1 during Jestha 2082, erratic efficiency readings in Ashadh–Shrawan 2082, and excessive overloading of T2 in Mangsir 2082 beyond allowable limits are all highlighted by the combined analysis of Figures 2 to 12. These results highlight the requirement for precise sensor calibration, dependable data collection methods, and ongoing condition monitoring to guarantee transformer dependability and safe operation over the long run.

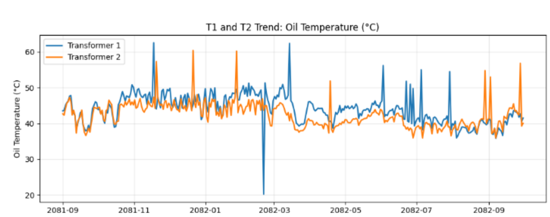

Figure 2: Variation of oil temperature

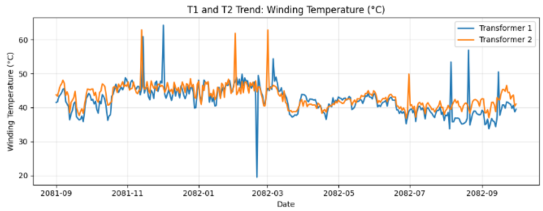

Figure 3: Variation of winding temperature

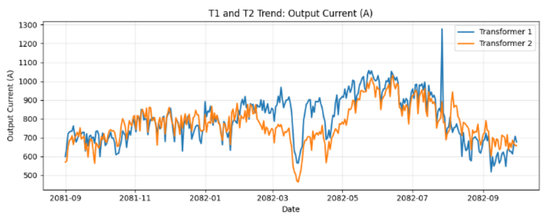

Figure 4: Variation of output current

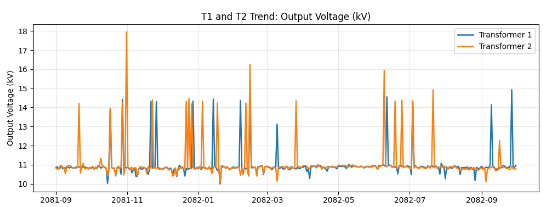

Figure 5: Variation of output voltage

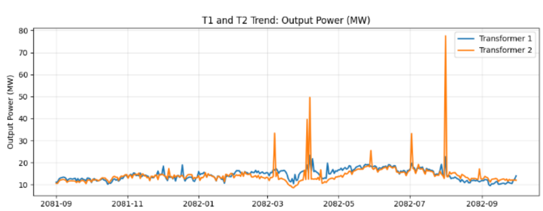

Figure 6: Variation of output power

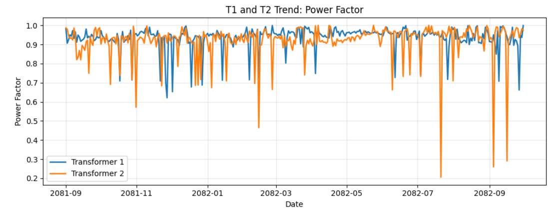

Figure 7: Variation of power factor

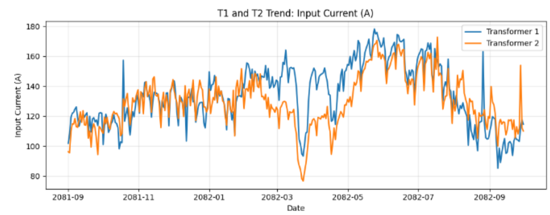

Figure 8: Variation of input current

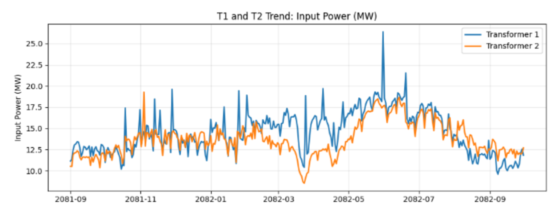

Figure 9: Variation of input power

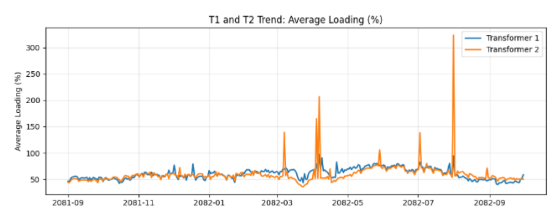

Figure 10: Variation of average loading

4.2. HI due to offline and online parameters

Figures 13 and 14 present the daily Health Index profile of Transformer 1 (T1) and Transformer-2 (T2) over the period of Poush 2081 to Poush 2082 (B.S.), distinguishing online (ON) and offline (OFF) contributions to overall condition. For T1 (Figure 13), the ON-state HI, reflecting real-time loading, efficiency, and thermal stress, varies widely between 0.35 - 0.90, with frequent variations during Poush 2081–Poush 2082 and concentrated dips in Magh-Falgun 2081, Jestha-Ashadh 2082, and slightly less for the period of Ashoj, Kartik, and Mangsir 2082 due to higher loading, efficiency deviations, and increased winding temperatures, indicating transient periods of accelerated insulation aging. Partial recovery occurs in Poush- Magh 2081, at the middle of Jestha and Mangsir- Poush 2082, ON-state HI stabilizes with fewer deep dips, while OFF-state HI remains consistently higher (0.70 - 0.78), showing the assessed health is well-maintained and de-energization reduces thermal/electrical stress. For T2 (Figure 14), ON-state HI fluctuates within 0.30 - 0.85, with sharp drops to 0.30 - 0.35 during at the middle of Chaitra 2081, Jestha, Shrawan and Poush of 2082, reflecting operational sensitivity and transient overloads, whereas OFF-state HI remains stable around 0.72 - 0.78, confirming good baseline health. There is the certain abrupt declination in the HI due to offline parameters at the month of Ashadh, Shrawan, Ashoj, Kartik and Mangsir 2082. The deviations between the ON and OFF HI for both transformers

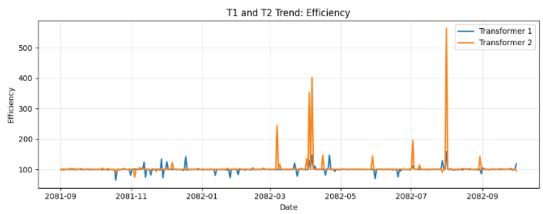

Figure 11: Variation of efficiency

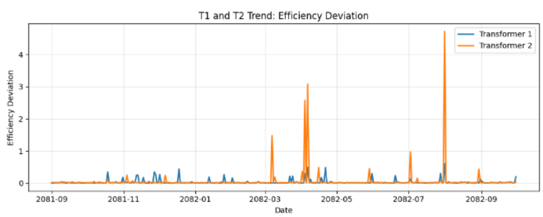

Figure 12: Variation of efficiency deviation

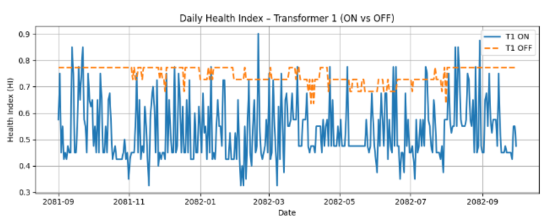

Figure 13: Variation of HI due to offline and online parameters for T1

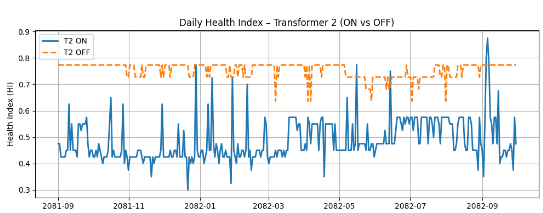

Figure 14: Variation of HI due to offline and online parameters for T2

highlights that day-to-day and seasonal variations in apparent condition are largely driven by operational and loading factors rather than irreversible material degradation, emphasizing the importance of continuous online monitoring, season-aware load management, and targeted preventive maintenance to mitigate cumulative thermal and insulation stress, particularly during high-load periods and abnormal conditions.

4.3. Analysis of monthly averaged ON–OFF health index profile

Figure 15 presents the month-wise averaged HI of T1 and T2 under ON and OFF parameters conditions from Poush 2081 to Poush 2082, providing insight into operational stress versus inherent transformer condition. During at the starting of Poush 2081 and Mangsir 2082, T1's ON-state HI shows abruptly changing to the peak, while OFF-state HI remains stable but slightly decrease in HI during the Shrawan – Kartik 2082 which indicate that the HI is poor for there months. The ON-state HI of T1 gradually declines, reaching minima in Falgun–Chaitra 2081. T2 shows a similar but more stable trend with lower values of HI due to ON parameters. In Baisakh–Jestha 2082, both transformers partially recover ON-state HI values as thermal and electrical loading decreases and reaches to the maximum value at the month of Kartik 2082, with minor OFF-state shifts reflecting residual thermal effects rather than insulation degradation. During Ashadh - Shrawan 2082, ON-state HI stabilizes with reduced variance due to moderated seasonal loads, and by Bhadra - Mangsir 2082, ON-state HI attains higher, consistent values, while OFF-state HI remains steady, indicating sustained insulation integrity and oil quality. The persistent gap between ON- and OFF-state HI highlights the difference between transient operational stress and long-term asset condition. The monthly HI variations due to offline and online parameters are as shown in Table 8.

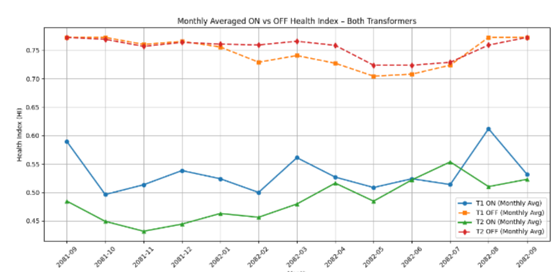

Figure 15: Variation of averaged monthly HI due to offline and online parameters

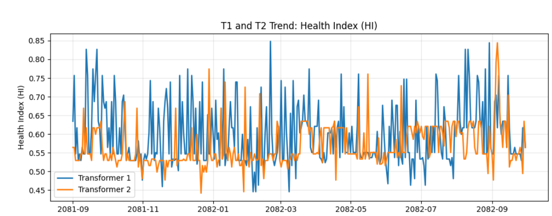

Figure 16: Variation of daily overall HI

4.4. Overall HI for T1 and T2

Figures 16 and 17 illustrate the daily and monthly overall HI trends of T1 and T2 from Poush 2081 to Poush 2082 (B.S.), highlighting comparative condition and operational stress. Daily HI trends (Figure 16) show that T1 consistently maintains slightly higher values,

Table 8: Month-wise comparison of monthly averaged ON–OFF Health Index (HI) for T1 and T2

Month (B.S.)	T1 ON HI	T1 OFF HI	T2 ON HI	T2 OFF HI
Poush 2081	0.59	0.78	0.48	0.77
Magh 2081	0.50	0.78	0.45	0.77
Falgun 2081	0.51	0.77	0.43	0.76
Chaitra 2081	0.54	0.77	0.44	0.77
Baisakh 2082	0.52	0.76	0.46	0.76
Jestha 2082	0.50	0.77	0.45	0.76
Ashadh 2082	0.56	0.78	0.48	0.77
Shrawan 2082	0.53	0.76	0.52	0.73
Bhadra 2082	0.51	0.72	0.49	0.71
Ashwin 2082	0.52	0.72	0.52	0.72
Kartik 2082	0.51	0.73	0.55	0.73
Mangsir 2082	0.61	0.77	0.51	0.76
Poush 2082	0.53	0.78	0.52	0.78

generally ranging 0.45 - 0.85, reflecting better health and resilience despite wider short-term fluctuations due to its primary load role. T2 operates within a narrower band (0.50 - 0.65) but exhibits more frequent dips compared to T1, notably Chaitra- Jestha, Shrawan and at the start of Poush 2082. Monthly HI trends (Figure 17) are in the similar manner as in daily HI. More noticeable decline in the month of Jestha and Bhadra for T1 and in the months Falgun 2081 for T2. After this month The HI gets increased for T2. The overall HI due to offline and online parameters are calculated based on the averaged sum of daily online and online HI. The calculated values are as in the Figure 18. Due to offline and parameters the overall HI is obtained based on the Equation 7 as in Table 8. The recommended actions are mentioned in Table 9 is from Table 4.

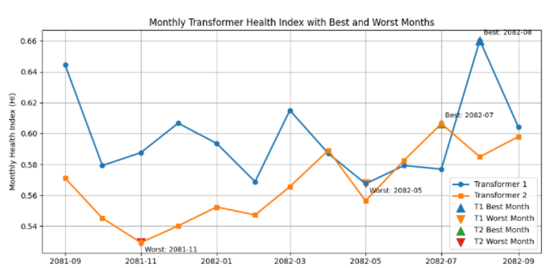

Figure 17: Variation of monthly overall HI indicating best and worst months

Both transformers fall within the fair health status, indicating satisfactory operation with observable signs of moderate aging or operational stress. Although no immediate corrective maintenance is required, the results justify enhanced inspection frequency and targeted diagnostic testing, particularly following periods of elevated loading or thermal stress, to prevent progression toward

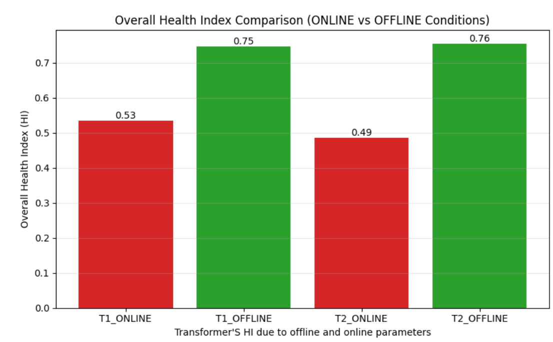

Figure 18: Overall HI due to online and offline parameters

adverse health states.

4.5. Overall HI degradation rate

Figures 19 and 20 depict the daily and monthly Health Index degradation rates of T1 and T2 from Poush 2081 to Poush 2082, illustrating the dynamics of condition change. Daily HI degradation rates (Figure 19) generally oscillate around zero for both transformers, indicating reversible, transient effects rather than sustained deterioration. T1 has more fluctuations up to $\pm$ 0.25 - 0.30, particularly during Mangsir 2081 and Falgun – Chaitra, Jestha and Kartik to Poush 2082, reflecting its exposure to variable and higher loading, while T2 remains within $\pm$ 0.15 - 0.20, showing smaller, more consistent fluctuations but abrupt change in the month of Jestha. Positive spikes indicate recovery, whereas negative spikes correspond to elevated operational stress. Monthly degradation rates (Figure 20) also center around zero, confirming dominance of short-term reversible effects over irreversible aging. T1 exhibits greater monthly variability (- 0.06 to + 0.08), with notable recovery from

Table 9: Overall Health Index (HI) for T1 and T2

Transformer	Overall HI	Health Status	Recommended Action
T1	0.598	Fair	Increase inspection and diagnostic testing
T2	0.567	Fair	Increase inspection and diagnostic testing

Falgun 2081 - Jestha 2082 and Bhadra to Kartik 2082, and sharp drops in 2082 Jestha and Shrawan. T2 fluctuates within a narrower band (- 0.03 to + 0.025), with its largest negative deviation in Bhadra 2082. Thus, neither transformer shows continuous health decline; T1's higher variability highlights short-term stress sensitivity, while T2's uniform trend suggests minor cumulative aging, recommending ongoing monitoring.

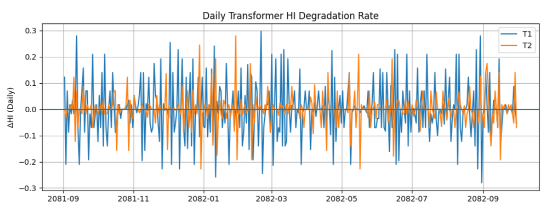

Figure 19: Variation of daily overall HI degradation rate

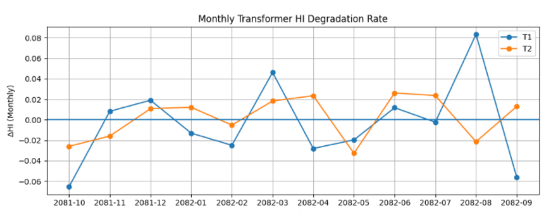

Figure 20: Variation of monthly overall HI degradation rate

5. Conclusion and limitations

This paper presented a practical SCADA-based transformer Health Index framework that explicitly separates online operational stress (ON-HI) from offline asset condition (OFF-HI). The methodology was validated using one year of SCADA data from two parallel 66/11 kV, 30 MVA power transformers operating under identical system conditions. A rule-based and explainable scoring approach was adopted to ensure transparency and utility applicability. The results show that ON-HI exhibits significant variability, driven by real-time loading, thermal stress, efficiency deviation, and power factor fluctuations, while OFF-HI remains largely stable throughout the study period. The ON-HI ranged from 0.35–0.90 for Transformer-1 and 0.35–0.85 for Transformer-2, whereas OFF-HI remained within 0.72–0.78 for both units, indicating no significant long-term insulation deterioration. Temporary reductions in ON-HI were observed during high-stress periods followed by recovery in subsequent months, confirming that the observed degradation was predominantly operational and reversible. The overall HI values of 0.598 for T1 and 0.567 for T2 place both units in the "Fair" health category, suggesting satisfactory operation with moderate aging effects. Degradation-rate analysis further confirmed the absence of continuous deterioration, as both daily and monthly HI degradation rates oscillated around zero. T1 exhibited higher short-term HI volatility due to greater load variability, while T2 consistently showed lower HI values, indicating a comparatively higher cumulative aging risk. Overall, the proposed framework provides a cost-effective, transparent, and SCADA-compatible tool for transformer condition monitoring and asset management. The clear distinction between operational stress and inherent asset condition enhances diagnostic confidence and supports condition-based maintenance decisions. The methodology is particularly suitable for utilities with limited access to advanced online diagnostic systems and can be readily integrated into existing asset management practices.

The validation is based on only two identical transformers from a single substation, limiting broader generalization across different ratings, technologies, and climatic conditions. The methodology depends strongly on SCADA data quality, and measurement errors, synchronization issues, or sensor faults can affect HI accuracy despite preprocessing. Advanced diagnostic techniques such as Dissolved Gas Analysis, Partial Discharge, and Frequency Response Analysis were not quantitatively incorporated, which may reduce fault detection specificity for internal defects. Additionally, the weighting scheme and threshold-based scoring remain fixed and expert-defined, requiring possible recalibration for different utilities or transformer types. The framework focuses on condition monitoring and degradation tracking rather than probabilistic failure prediction, remaining life estimation, or risk-based economic optimization. Finally, the one-year dataset may not fully represent long-term insulation aging behavior, and multi-year validation would improve lifecycle assessment robustness.

Author contributions

Conceptualization- M.N. and P.P.S.; Methodology- M.N. and P.P.S.; Investigation- M.N., P.P.S., P.B.A., S.M. and N.K.; Resources- M.N.; Supervision- P.P.S.; Visualization- M.N., P.P.S, P.B.A.; Writing—original draft preparation- M.N.,P.P.S., P.B.A, S.M., and N.K.; Writing- review and editing- M.N. and P.P.S.

Data availability

The data supporting the findings of this study are available from the Nepal Electricity Authority. Restrictions apply to the availability of these data, which were used under permission for the current study and are not publicly available.

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Conflicts of interest

The authors declare no conflict of interest.

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